# Structural Factor-Augmented VAR (SFAVAR) and the Effects of Monetary Policy*

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**Abstract**

Factor-augmented VARs (FAVARs) have combined standard VARs with factor analysis to exploit large data sets in the study of monetary policy. FAVARs enjoy a number of advantages over VARs: they allow a better identification of the monetary policy shock; they can avoid the use of a single variable to proxy theoretical constructs, such as the output gap; they allow researchers to compute impulse responses for hundreds of variables. Their shortcoming, however, is that the factors are not identified and, therefore, lack any economic interpretation.

This paper seeks to provide an interpretation to the factors. We propose a novel Structural Factor-Augmented VAR (SFAVAR) model, where the factors have a clear meaning: "Real Activity" factor, "Price Pressures" factor, "Financial Market" factor, "Credit Conditions" factor, "Expectations" factor, etc. The paper employs a Bayesian approach to extract the factors and jointly estimate the model. This framework is then suited to study the effects on a wide range of macroeconomic variables of monetary policy and non-policy shocks.

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# 1 Introduction

Vector autoregressions (VARs) are a standard framework to study the effects of monetary policy shocks on macroeconomic variables. VARs often serve also as benchmarks to which the implications of theoretical models can be compared. The empirical success of theoretical models is then assessed on the basis of how well the models' impulse responses can approximate those derived from an a-theoretical VAR. With few exceptions, VAR models employed in the literature are fairly small to save degrees of freedom. Typical monetary VARs include a measure of output or the output gap, a measure of inflation, the federal funds rate, and few other variables[1]. The small number of variables, however, is at odds with the information set actually available to central banks. In reality, central banks monitor a huge amount of economic data and indicators. Since researchers use VARs to identify monetary policy innovations, a failure to account for the appropriate information set available to the policymaker in real-time would be problematic. Innovations would be, in fact, incorrectly measured.

Recent research has therefore attempted to incorporate larger information sets in VAR models. Bernanke and Boivin (2003) and Bernanke, Boivin and Eliasz (2005) combine VAR models with factor analysis to measure the effects of monetary policy in what they define a "data-rich" environment. Their contribution is the use of Factor-Augmented VARs (FAVARs), in which they add common factors to a standard VAR specification. But what are the factors? It is well known that factors cannot be uniquely identified. The main drawback of the FAVAR approach is, in fact, the impossibility to assign

[1] Christiano,Eichenbaum and Evans (2000) is a standard reference. Leeper, Sims, and Zha (1996), using Bayesian methods, manage to estimate larger VARs, but still with less than 20 variables.

any sort of economic interpretation to the factors.

Our paper follows this literature and tries to go a step further, seeking to provide a structural interpretation to the factors.

We analyze monetary policy and the dynamics of the economy, but exploiting more information than typical in VAR analysis. We start from Bernanke and Boivin (2003) and Bernanke, Boivin, and Eliasz (2005)'s FAVAR approach, and we try to individuate plausible restrictions that allow us to give a structural interpretation to the factors. That is, we seek to identify each factor as a basic force that governs the economy as 'real activity', 'price pressures', 'financial market sector', 'credit sector', and so on. We therefore propose a vector autoregression augmented with economically interpretable (and in this sense more 'structural') factors: we label this novel approach Structural Factor-Augmented VAR (SFAVAR).

Our proposal shares FAVAR's advantages over standard VARs. First, as also Bernanke, Boivin, and Eliasz (2005) emphasize, if central banks and the private sector had information beyond that included in the VAR, the measurement of the unsystematic part of monetary policy would be incorrect. Factor-augmented VARs allow, instead, a better identification of the monetary policy shock, since they condition on a more realistic information set. Also, in low-dimensional VARs impulse responses can be derived only for the few included variables. Factor-augmented VARs permit to observe the impulse responses to shocks for all the economic series included in the construction of the factors.

Compared with existing FAVAR approaches, instead, our approach allows us to assign a clear economic interpretation to the factors. This was not possible in FAVAR models, as also recognized and discussed in Bernanke and Boivin (2003).

Furthermore, the proposed Structural FAVAR can be a useful tool for the policy maker. Indeed, Sims (2002) poses the problem that existing econometric approaches fail in treating the huge amount of data central banks consider when deciding their actions. Sims emphasizes the role of sectorial experts, disaggregated variables, local economical dynamics in deciding policy. Our approach enables one to exploit all these data to infer the state of the economy, helping the understanding of the main forces driving the movements of the variables, and therefore the choice of optimal policy.

We derive the factors using Bayesian methods. We estimate the system jointly by likelihood methods, using Gibbs sampling: therefore, we exploit the VAR dynamics to extract the factors. A similar methodological approach has been followed by Bernanke, Boivin, and Eliasz (2005), and Kose, Otrok, and Whiteman (2000). In the factor analysis literature, standard approaches have been the derivation of factors through principal components, as in the approximate factor model of Stock and Watson (2002), and with spectral analysis, as in Forni, Hallin, Lippi and Reichlin (2000). In those cases, estimation works in two steps. First, the factors are extracted, then they are taken as given for the estimation. A particular advantage of our Bayesian approach is that it facilitates the introduction of restrictions on the loadings, making the economic interpretation of the factors possible. With this procedure, we can also accompany the factors with an accurate indication of the uncertainty surrounding their estimation. Compared with FAVAR models, where principal components are derived and then the VAR is estimated taking the principal components as certain (as in Bernanke and Boivin 2003, but not Bernanke, Boivin, and Eliasz 2005), therefore, our Bayesian procedure allows us to obtain a more accurate indication of the total uncertainty in the estimation.

We include in the analysis several economically interpretable – or 'structural' – factors: a real activity factor, which we deem more suitable to capture the theoretical and unobservable macroeconomic concept of 'output gap' rather than a single observable variable, an inflation factor, a long-term interest rates factor, a financial market factor, and money and credit factors. In this way, the factors carry an economic meaning. Another original characteristics of the framework we propose is the insertion of an expectations factor in the VAR. The inclusion of such a factor may potentially lead to useful insights in the study of the interactions between the real economy and expectations, also permitting to assess if expectations move in accordance with the rational expectations hypothesis.

Recent papers seek to build structural factor models. Forni *et al.* (2004) use their proposed structural factor model to revisit standard results in the structural VAR literature, identifying the response of macroeconomic variables to a long-run (productivity) shock. Yet the factors lack an economic interpretation but their model is structural in the same way common SVARs are. Justiniano (2004) also exploits Bayesian methods to derive factors that can be interpreted as country-specific shocks.

We evaluate the response of a wide range of macroeconomic variables and factors to monetary policy and other shocks. We also show that adding factors to a standard Taylor rule can significantly improve its fit as a description of post-war U.S. monetary policy. The result indicates that the Federal Reserve is actually responding to a larger amount of information than currently assumed by previous studies. The Bayesian approach to extract the factors is extremely flexible and it can be exploited to impose alternative restrictions on the loadings to study different issues. An interesting extension, for example, would consist of using long-run restrictions to identify the impulse responses to technology shocks (which have an effect in the long-run) and demand shocks (which have no effect in the long-run), in the context of our SFAVAR framework. Similarly the model may be used to study the effects of region-specific versus country-specific shocks (for example, in the Euro area context).

The rest of the paper is organized as follows. Section 2 describes the model and the restrictions we use to identify the factors. Sections 3 and 4 discuss the principal components and Bayesian approaches to estimation, respectively. The empirical framework is illustrated in section 5, where we introduce our structural factors and SFAVAR estimation. Section 6 reports and discusses our results. Policy reaction functions under the traditional framework and a large information environment are described in Section 7. Section 8 concludes.

# 2 The Model

Let $Y_t$ and $X_t$ be two vectors of economic variables, with dimensions $M \times 1$ and $N \times 1$, and where $t = 1, 2, ..., T$ is a time index. $Y_t$ denotes the policy instrument controlled by the central bank, such as the Federal Funds rate in the U.S. case, and $X_t$ is a large data set of economic variables. Assume that there exist some unobservable fundamental forces that affect the dynamics of $X_t$, which can be summarized by a $K \times 1$ vector of factors $F_t$, so that

$$X_t = \Lambda F_t + e_t \tag{1}$$

where $e_t$ are errors with mean zero and, for now, possibly weakly correlated. Take a partition of $X_t$, say $X_t^1, X_t^2, ..., X_t^I$, where $X_t^i$ is a $N_i \times 1$ vector and $\sum_i N_i = N$. Assume that each of the vectors $X_t^i$ is now explained by only some of the elements of the vector $F_t$. That is, there is a partition of $F_t$ given by $F_t^1, F_t^2, ...F_t^I$ where $F_t^i$ is a $K_i \times 1$ vector, $\sum_i K_i = K$ and $K_i < N_i$. Also, assume that $X_t^i$ is explained by only $F_t^i$. Hence we have

$$\begin{bmatrix} X_t^1 \\ X_t^2 \\ ... \\ X_t^I \end{bmatrix} = \begin{bmatrix} \Lambda_1^f & 0 & ... & 0 \\ 0 & \Lambda_2^f & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & \Lambda_I^f \end{bmatrix} \cdot \begin{bmatrix} F_t^1 \\ F_t^2 \\ ... \\ F_t^I \end{bmatrix} + \begin{bmatrix} e_t^1 \\ e_t^2 \\ ... \\ e_t^I \end{bmatrix} \tag{2}$$

where $\mathbb{E}\left[e_t^i e_t^j\right] = 0$ for all $i$, $j = 1, ..., I$ and $i \neq j$. The restriction we impose on the model is that each of the variables in the $X_t$ vector is influenced by the state of the economy only through the corresponding factors. For the rest of the paper, we assume that each segment of $X_t$ is explained by exactly one factor, that is $K_i = 1$ for all $i$.

Also assume that the dynamics of $\left(Y_t, F_t^1, F_t^2, ...F_t^I\right)$ is given by a factor-augmented autoregression (FAVAR):

$$\begin{bmatrix} F_t^1 \\ F_t^2 \\ ... \\ F_t^I \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1}^1 \\ F_{t-1}^2 \\ ... \\ F_{t-1}^I \\ Y_{t-1} \end{bmatrix} + \nu_t \tag{3}$$

where $\Phi(L)$ is a conformable lag polynomial of finite order $d$ and $\nu_t$ is an error term. Clearly, the difference between this model and a standard VAR is the presence of unobservable factors.

Our main contribution is given by the set of restriction illustrated in equation (2). Indeed, assume that the vector of economic variables $X_t$ is divided in subsets of similar variables. For example, a subset of variables related to the real activity, a subset of variables related to inflation, and so on. The common force that moves these variables, i.e. the dynamic factor, is now economically interpretable. For instance, these forces represent wide concepts such as economic activity or basic movements in prices, and so forth.

Bernanke, Boivin, and Eliasz (2005) provide a motivation for a standard FAVAR model (where the factors do not have an immediate economic interpretation) in the context of a simple macroeconomic model, to explain why researchers need to condition their models on a richer information set. As a model of central bank's behavior, our framework assumes that the central bank observes only the policy instrument $Y_t$ (the federal funds rate) and a large set of noisy indicator variables $X_t$. Alternative information assumptions, however, are easily introduced in such a framework.

Our SFAVAR approach has some advantages over estimation of simple VARs on the observed data. First, using factors may reduce measurement problems.[2] Indeed some factors are extracted by similar variables, such as disaggregate or regional versions of the main variable. For instance, a 'Real Activity' factor can be extracted, among other series, from 'New Orders in durable good industries' as well as 'New Orders in non-defense capital goods'. But what is the nature of the structural factors? We believe that factors are more than simple re-aggregation of variables. Indeed, in our model the loadings are also unknown and need to be estimated. Hence, what criteria should the model use when fixing the loadings?

The Bayesian joint estimation of equations (2) and (3) helps answering this question.

Factors are the unobserved variables that determine at the same time the value of all the other variables in the economy and the dynamics of the whole economy. Indeed each factor, through equation (2), is the sole responsible for today's value of the variables related to it, with the exception of an idiosyncratic error. This error is given by measurement errors as well as true idiosyncratic (i.e. relative to a single sector or region) shocks to the single

[2] Factor models are widely used to deal with measurement errors.

variable.

Factors, together with the policy instrument, also enter in the VAR equation (3). That is, given the state of the economy today, the future depends only on the level of current and past values of the factors and policy instruments. All the idiosyncratic shocks will be 'reabsorbed'. That is, we expect that an idiosyncratic shock to a single variable will not affect the path of the economy.

Continuing the example of the 'Real Activity' factor, it may be that for a few months 'New Orders in durable good industries' may be well above average. But this does not necessarily mean that the whole economy will be affected by such sectorial shocks. But in our framework this is equivalent to say that we do not expect the general level of production, inflation, or of the other fundamental forces of the economy, to be affected. Hence, with our estimation we try to 'clean' the dynamics of the observed variables to find the main interactions between the different parts of the economy.

Because of this interpretation, our model may be more robust to the modifications of the economic reality, which can also help for forecasting purposes.

The fact that our factors not only have an economic interpretation, but can represent better description of the state of the economy than single observable variables, leads us to call this approach Structural FAVAR (SFAVAR).

We now describe two procedures for the estimation of the factors and of the parameters of the model: Principal Components and Bayesian joint estimation.

# 3 Principal Components Estimation

The first method we use to estimate the model is Principal Components. As will become clear later, we perform Principal Components (PC) estimation to obtain a reasonable guess of the model parameters to be used in the joint estimation. We will not present the results we obtain with PC.

The reason we prefer the Bayesian joint estimation to principal components, is that the principal components approach constructs the estimated factors using only (2) and thus ignoring the restrictions on the dynamics of the factors given by (3): as discussed by Eliasz (2002), the factors estimated by PC have unknown dynamic properties. Loosely speaking, the factors estimated by PC are an unknown moving average of some more fundamental factors, where the fundamental factors are identified through the VAR dynamics. As we have already discussed, considering the dynamics of the factors is important for their estimation and interpretation. Moreover, the apparently higher complexity of the Bayesian joint estimation is repaid by an easier and theoretically clear assessment of the level of uncertainty: the error bands are simple to construct and to interpret.

Also note that the number of variables in each sub-segment $X_t^i$ can be rather small. Therefore, were we using PC, the standard asymptotic results would no longer hold (we know, in fact, that PC give consistent estimates when $T$ and $N \rightarrow \infty$). This complication does not arise in the Bayesian approach.[3]

The results under the PC approach, however, are not too far from those with Bayesian joint estimation.

To estimate the factors with PC we follow Bernanke, Boivin, and Eliasz

[3] Advantages of principal components estimation, instead, lie in its computational simplicity and its semi-parametric, rather than fully parametric, approach.

(2005) two-step procedure. The identification of the factors is obtained by imposing $F^{i\prime}F^{i}/T = I$.

The procedure is described in Appendix A.

# 4 Bayesian Approach: Joint Estimation

The model can be written as:

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \Lambda & 0 \\ 0 & I_M \end{bmatrix} \begin{bmatrix} F_t \\ Y_t \end{bmatrix} + \begin{bmatrix} e_t \\ 0 \end{bmatrix} \tag{4}$$

where $\Lambda$ has all the restrictions we have imposed. Also:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi\left(L\right) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \nu_t. \tag{5}$$

Assume that $e_t \sim$i.i.d.$N\left(0, R\right)$ where $R$ is diagonal. Also assume that $\nu_t \sim$ i.i.d.$N\left(0, Q\right)$ and $v_t$ and $e_t$ are independent. Following Eliasz (2002) and Bernanke, Boivin, and Eliasz (2005), we can apply a Bayesian likelihood approach. To identify the factors, we impose the restriction that the first element of $\Lambda_i^f$ is one for all $i$'s.

The estimation procedure is discussed in Appendix B.

# 5 Empirical Framework

In the previous sections, we have presented the theoretical framework that enables a structural interpretation of the factors and leads to the definition of Structural Factor-Augmented VARs (SFAVAR). In the rest of the paper, we apply this novel SFAVAR approach to study the effects of monetary policy.

## 5.1 Structural Factors

We partition the vector of economic variables $X_t$ so that each variable is explained by one of the following structural factors:

- **REAL ACTIVITY factor**. This factor can be re-conducted to the theoretical macroeconomic concept of 'output gap', providing a summary of the real activity situation. It determines variables such as industrial production, capacity utilization rates, employment/unemployment indicators, inventories stocks, new and unfilled orders, consumer expenditures, and so on.

- **INFLATION factor**. It indicates a broader concept of inflation, incorporating data from the evolution of a variety of consumer prices, producer prices, wages, oil price, and so forth.

- **INTEREST RATES factor**. This factor explains a number of public and private bonds interest rates at different maturities.

- **FINANCIAL MARKET factor**. The introduction of this variable in our SFAVAR model is motivated by the recent interest in seeking to evaluate whether monetary policy responds to movements in asset prices (among other studies, see Bernanke and Gertler 2001); moreover, this permits us to verify the existence and the relevance of a financial market channel of monetary policy transmission.

- **MONEY factor**. It explains a number of money stock variables, together with data on deposits, bank reserves and other similar variables.

- **CREDIT factor**. It explains many private credit and loans variable. With this factor, we are able to verify the empirical importance of the credit channel of monetary transmission. This represents a potentially important channel and it is usually disregarded in standard VAR analysis.

- **EXPECTATIONS factor**. The introduction of expectations is another original feature of the proposed framework. Expectations regarding production, employment, inventories, new orders (derived from NAPM surveys), future inflation and future short-term rates (via surveys and interest rate spreads), are all considered. The dynamics of expectations with respect to the other variables of the system is an interesting issue to examine.

The complete list of variables explained by each factor is reported in Appendix C.

Finally, we assume that $Y_t$, the policy variable, is exogenously set by the central bank. The policy measure, in our case, is the Federal Funds rate.

## 5.2 SFAVAR Estimation

The data set builds upon the balanced panel employed by Stock and Watson (2002). Their data set consists of 120 monthly economic time series, for a sample starting in January 1959 to December 1998. To this panel of data we add several other variables, mainly for the money and credit sectors. All these additional data are taken from FRED, the database of the Federal Reserve Bank of Saint Louis, or from Datastream.

Therefore, we end up with a balanced data set consisting of 185 variables for estimation, spanning the period 1959:01-1998:12. All the series have been transformed to reach stationarity and seasonally adjusted, if necessary. The series have been demeaned and standardized. Our data set with the complete list of variables divided into segments, the source, and the relevant transformations applied, is reported in Appendix C.

In the VAR, we consider 13 lags for all the variables to allow sufficient dynamics.

We jointly estimate the system (13)-(14) by Gibbs sampling as illustrated in section 4. The total number of parameters and factors to be estimated is 5,073, so that we have approximately 19 data points for each parameter. The estimates are based on 5,000 draws, with the first 2,000 omitted to reduce the influence of the initial guess on final results.

To evaluate the convergence of the Gibbs sampler, we plot the factors calculated from the first half of the kept draws, together with those derived from the second half. We also plot selected impulse response functions (whose specifications will be discussed later) calculated from the first half of the kept draws, together with those derived from the second half. Figure 1 and 2 suggest that convergence has been achieved.

We calculated also the autocorrelations of parameters within each parameter chain: the autocorrelations are small. We perform, then, the Raftery-Lewis test[4]. This suggests a thinning parameter of 1, an initial burn-in of 3 draws and a total number of draws to achieve the desired accuracy of 1,035 draws. Our choice to perform 5,000 draws omitting the first 2,000 seems therefore safe.

# 6 Results

Having assigned an economic interpretation to the factors, a first interesting thing to do is to analyze their dynamics. Figure 3 shows the estimated factors. The factors obtained from Gibbs sampling are not far from those derived from the principal components estimation. Differences, however, exist: the correlations between the two estimates range from 0.81 for Money, to 0.99 for the Interest Rates factor.

Together with the factors, the graph shows the 95% probability bands.

[4]See Raftery and Lewis (1992).

This is another novel feature of the proposed approach that makes simpler the evaluation of the uncertainty characterizing the factors. In our case, the error bands are almost indistinguishable from the estimated series, signalling that factors are sharply derived; some uncertainty characterizes only the estimate of the Expectations (and to a lesser extent Money and Inflation) factor.

In figure 4, we plot the estimated loadings for each factor. We can notice that the factors do not just closely follow a single variable; the loadings are spread across many series.

Now that we have derived economically interpretable factors, we can examine their reaction, and the reaction of the several variables used in their construction, to a monetary policy shock. We identify the system by means of a Cholesky decomposition[5]. We therefore need to recursively order the variables. One problem arising from our system is the presence of an Interest Rates factor, which includes data on several long-term rates. Allowing our policy rate to respond to several market rates would potentially lead to indeterminacy. We would face an identification problem, running the risk of confusing an arbitrage condition with the policy rule. This issue is discussed in greater detail in Leeper, Sims and Zha (1996). In a similar context, they assume that the policy maker can observe and react to the state of the economy. Therefore, variables containing expectations on the economy, such as long-term rates, do not contain additional information besides what is directly observed. For this reason, we similarly assume that the monetary authority does not react to the Interest Rates factor.

Following the same line of reasoning, assuming that it is possible for the monetary authority to observe the current state of the economy, we exclude

[5] Other identification schemes are possible and can be easily accommodated in our framework, for example exploiting long-run restrictions. Here, we keep the computational costs at a minimum, by employing a simpler Cholesky decomposition.

a contemporaneous response of the policy rate to Expectations. For the Cholesky ordering, the Interest Rates factor and Expectations are therefore ordered after the Federal Funds rate.

A contemporaneous response of $Y_t$ is, instead, permitted to the other factors (while these factors can react to policy only with a lag). We consider the following ordering of factors: Inflation, Real Activity, Credit, Money, Financial Market, Federal Funds rate, Interest Rates and Expectations. Note that even if monetary and financial variables are likely to react faster than one or two months to policy innovations, Federal Funds rate changes happen after FOMC meetings, which take place, in the case of the Fed, approximately every six weeks: being the variables monthly averages, a response within the same month would be incorrect if the meeting is not held in the first days of the month. Different orderings have been tried and the main results were substantially unchanged.

Figures 5-12 show the derived impulse responses for all the variables and to all the shocks in the system. The impulse responses display the dynamics of the economy after a one standard deviation shock to each variable. Note that the scale has been normalized to one standard deviation for each to facilitate comparison. Error bands represent 68% probability bands (i.e. approximately one-standard-error bands). These are derived as the $16^{th}$ and $84^{th}$ percentile of the obtained response functions from Gibbs sampling. This procedure gives us a more accurate indication of the total uncertainty, since it includes also uncertainty surrounding the estimation of the factors.

A particular advantage of the factor-augmented framework is that we can derive impulse responses not only for the fundamental factors, but also for all the variables explained by factors. We provide impulse responses to a monetary policy shock for some of the most interesting variables in Figures

13-14.

The estimated impulse responses generally display intuitive dynamics.

- Monetary policy shock

Starting from Figure 10, we can look at the reaction of the structural factors to a one standard deviation monetary policy shock. Inflation displays a small increase right after the shock and then declines significantly. Hence, we find some evidence of a 'price puzzle'. The price puzzle has usually been related to the omission of relevant information in the VAR. By incorporating the knowledge central banks have when setting policy, it is argued, the puzzle should disappear.[6] Notice, however, that we find a price puzzle even if our framework includes a measure of expectations and a rich information set. Our results are therefore more consistent with the existence of a cost channel of monetary transmission (see Barth and Ramey 2001). According to this theory, a monetary contraction causes an increase in firms' marginal costs and therefore an increase in prices.

Real Activity drops, reaching the minimum one year after the shock, and then returns to the previous level after slightly more than two years, showing the usual hump-shaped behavior. Credit lags the Real Activity factor, showing a delay of about six months and a more sluggish response. Money shows a quick and persistent downward adjustment. The Financial Market factor quickly drops for about six months-one year.

After a monetary contraction, we notice an immediate downward adjustment of expectations, which after a semester-one year return to the previous level. The Expectations factor accounts mainly for inflation expectations: a monetary contraction is then interpreted by the private sector as a signal that future inflation will fall.

[6] This is usually accomplished by adding a commodity price measure in the VAR.

In Figure 13-14 we notice that a positive shock to the federal funds rate reduces industrial production, the capacity utilization rate, and to a lesser extent, inventories. The effect of monetary policy on unemployment duration seems small, whereas a monetary contraction produces a persistent reduction in vacancies, in the hours worked, and an increase in the unemployment rate. It reduces Inventories and it leaves Imports and Exports unaffected. Note also the big drop of M1 and the smaller one of M2.

- Financial Market shock

An interesting result that emerges from Figure 9 is that the central bank reacts to a positive shock to Financial Markets, typically an increase in asset prices. The Federal Funds rate increases and returns to its previous value only after about two-three years. Our framework appears to fit the idea of a financial boom: we have a shock to Financial Markets not supported by a similar increase in the fundamentals. Note also that after several months Real Activity is depressed following such a shock. We find reasonable to say that this is the cost of the central bank's reaction.

- Expectations shock

From Figure 12, we see that a shock to Expectations is not persistent (it quickly returns to zero); this is consistent with what predicted by the rational expectations hypothesis. The central bank reacts to the shock increasing the Federal Funds rate. This is evidence that the central bank responds to private sector expectations to maintain them anchored to the policy objectives. Such a reaction is consistent with the effort real world policy makers exercise in monitoring private expectations. A positive shock to Expectations also leads to a persistent increase in Inflation.

# 7 Policy Reaction Function

The behavior of the Federal Reserve is often described by a policy reaction function, where the policy instrument is adjusted according to the state of the economy. A standard specification that has proved quite successful in tracking U.S. monetary policy is the following Taylor rule with partial-adjustment:

$$i_t = \rho i_{t-1} + (1 - \rho)(\phi^{\pi}\pi_t + \phi^{y} y_t) + \varepsilon_t, \tag{6}$$

where the federal funds rate $i_t$ is set in response to deviations of inflation and output from their respective targets. The rule typically includes a partial-adjustment mechanism to match the smooth dynamics of interest rates observed in the data.

We consider an alternative in which the central bank is allowed to exploit a large amount of information. The policy rate is set on the basis of the state of the economy. The state of the economy is now summarized by our structural factors. The policy reaction function can then be expressed as:

$$i_t = \rho i_{t-1} + (1 - \rho)(\phi^{F}\mathbf{F}_t) + \varepsilon_t, \tag{7}$$

where $\mathbf{F}_t$ includes the factors to which monetary policy is assumed to respond, i.e. Real Activity factor, Inflation factor, Financial Market factor, Money factor, and Credit factor.

Table 1 and 2 report the estimates for the standard Taylor rule and the new policy rule with factors.

We notice the usual sluggish adjustment of the policy instrument, suggested by the coefficient $\rho$ very close to 1. We obtain Taylor rule coefficient values of 1.214 for inflation and 1.205 for the real activity measure.

But assume now that policy responds to a larger information set. Table 2 displays an estimated response to the inflation factor equal to 1.685, larger than the Taylor rule result. This indicates that the reaction to price pressures is somewhat stronger when we employ a broader measure of inflation. The response to real activity, instead, seems weaker (coeff.=0.980). We can observe a significant reaction of monetary policy to the Financial Market factor (coeff. 0.723). This finding, however, is probably hiding a strong reverse causality. We do not detect, instead, any significant reaction of policy to money and credit factors.

Bernanke and Boivin (2003) try to determine the existence of an excess policy response, including the fitted value $\widehat{i_t}$ derived from the rule with factors in the usual Taylor rule. Being this additional term significant, they conclude that an excess response indeed exists. This signals that there is omitted information in the traditional Taylor rule. We similarly aim to test whether the Fed actually exploits more information when setting policy. To compare the two rules, we employ a test of encompassing. We compute the fitted values from (6) and (7), and we call those values $\widehat{i_t^{Taylor}}$ and $\widehat{i_t^{Factors}}$, respectively. The test of encompassing – to choose between competing *non-nested* specifications – consists of a regression of the actual $i_t$ on the fitted values coming from the two formulations:

$$i_t = \alpha \widehat{i_t^{Taylor}} + (1 - \alpha) \widehat{i_t^{Factors}} + \nu_t. \tag{8}$$

We obtain:

$$i_t = \underset{(0.259)}{0.14} \widehat{i_t^{Taylor}} + \underset{(0.259)}{0.86} \widehat{i_t^{Factors}} + \nu_t, \tag{9}$$

where we can easily accept the hypothesis $\alpha = 0$ at all usual confidence levels. This outcome suggests that the Fed responds to a larger information set than commonly assumed in popular Taylor rules, in taking policy decisions. The omitted information in the standard Taylor rule appears to be mainly broader measures of inflation and real activity (provided instead by the factors), and financial market variables.

# 8 Conclusions

Recent research has combined VAR models with factor analysis, leading to advances in the measurement of monetary policy effects. This literature has permitted researchers to incorporate larger and more realistic information sets. The main shortcoming of this literature, so far, has been the inability to identify the factors, which lack an economic interpretation.

We have suggested a solution to this drawback, proposing a factor-augmented VAR where we provide a structural interpretation to the factors. The factors have a more immediate economic meaning, since they explain different subcategories of the data.

We have employed a Bayesian approach to estimate the factors jointly with the rest of the system, therefore exploiting the VAR dynamics to extract them. This approach has allowed us to study impulse responses that are obtained conditioning on a larger and more realistic amount of information. The paper also shows that a policy reaction function that responds to the proposed structural factors seems empirically more plausible in tracking the evolution of U.S. monetary policy than does a traditional Taylor rule with partial adjustment.

We believe that this approach can be useful to better model the central banks' decision environment, by providing a more accurate characterization of the large information set they can exploit.

In future research, we plan to incorporate more structure in our factor-augmented VAR, possibly assessing the response of macroeconomic variables to both technology and monetary shocks, or including the factors in theoretically-based general equilibrium models.

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# A Estimation with Principal Components.

The estimation works as follows.

1. Using principal components, we find the factors $\left(F_t^1, F_t^2, ...F_t^I\right)$ from the model

$$\begin{bmatrix} X_t^1 \\ X_t^2 \\ ... \\ X_t^I \end{bmatrix} = \begin{bmatrix} \Lambda_1^f & 0 & ... & 0 \\ 0 & \Lambda_2^f & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & \Lambda_I^f \end{bmatrix} \cdot \begin{bmatrix} F_t^1 \\ F_t^2 \\ ... \\ F_t^I \end{bmatrix} + e_t. \tag{10}$$

   We obtain $\left(\hat{F}_t^1, \hat{F}_t^2, ...\hat{F}_t^I\right)$.

2. We run a standard VAR

$$\begin{bmatrix} \hat{F}_t^1 \\ \hat{F}_t^2 \\ ... \\ \hat{F}_t^I \\ Y_t \end{bmatrix} = \Phi\left(L\right) \begin{bmatrix} \hat{F}_{t-1}^1 \\ \hat{F}_{t-1}^2 \\ ... \\ \hat{F}_{t-1}^I \\ Y_{t-1} \end{bmatrix} + \nu_t \tag{11}$$

We obtain $\hat{\Phi}\left(L\right)$.

3. To find the loadings, we do OLS of the equation

$$\begin{bmatrix} X_t^1 \\ X_t^2 \\ ... \\ X_t^I \end{bmatrix} = \begin{bmatrix} \Lambda_1^f & 0 & ... & 0 \\ 0 & \Lambda_2^f & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & \Lambda_I^f \end{bmatrix} \cdot \begin{bmatrix} \hat{F}_t^1 \\ \hat{F}_t^2 \\ ... \\ \hat{F}_t^I \end{bmatrix} + e_t. \tag{12}$$

   We obtain $\left(\hat{\Lambda}_1^f, \hat{\Lambda}_2^f, ..., \hat{\Lambda}_I^f\right)$.

# B Likelihood-Based Gibbs Sampling.

We want to estimate the parameters $\theta = (\Lambda, R, vec(\Phi), Q)$ and the factors $\{F_t\}_{t=1}^{T}$. We start from the state-space model in (4) and (5), where $\Lambda$ is restricted as described in the text, $e_t$ ~i.i.d. $N(0, R)$, $\nu_t$ ~i.i.d. $N(0, Q)$, $v_t$ and $e_t$ are independent and $R$ is diagonal. We can use Gibbs sampling to estimate the model. We closely follow Eliasz (2002), to whom we refer for more details.

We can rewrite the model defining $\mathbf{X}_t = (X_t', Y_t')'$, $\mathbf{F}_t = (F_t', Y_t')'$ and $\mathbf{e}_t = (e_t', 0, ..., 0)'$:

$$\begin{aligned} \mathbf{X}_t &= \mathbf{\Lambda}\mathbf{F}_t + \mathbf{e}_t && (13) \\ \mathbf{F}_t &= \Phi(L)\mathbf{F}_t + \nu_t && (14) \end{aligned}$$

where $\mathbf{e}_t$ ~i.i.d.$N(0, \mathbf{R})$, $\mathbf{\Lambda} = \begin{bmatrix} \Lambda & 0 \\ 0 & I_M \end{bmatrix}$, $\mathbf{R} = \begin{bmatrix} R & 0 \\ 0 & 0_M \end{bmatrix}$.

Recall that $\Phi(L)$ is of finite order $d$. We want to rewrite the VAR as a first-order Markov process. Let $\Phi(L) = \Phi_1 L + \Phi_2 L^2 + ... + \Phi_d L^d$. Define $\bar{\mathbf{F}}_t = \left(\mathbf{F}_t', \mathbf{F}_{t-1}', ..., \mathbf{F}_{t-d+1}'\right)'$, $\bar{v}_t = (\nu_t, 0, ..., 0)'$,

$$\bar{\Phi} = \begin{bmatrix} \Phi_1 & \Phi_2 & ... & \Phi_{d-1} & \Phi_d \\ I_{(K+M)} & 0 & ... & 0 & 0 \\ 0 & I_{(K+M)} & ... & 0 & 0 \\ ... & ... & ... & ... & ... \\ 0 & 0 & ... & I_{(K+M)} & 0 \end{bmatrix} \qquad (15)$$

and so we get

$$\bar{\mathbf{F}}_t = \bar{\Phi}\bar{\mathbf{F}}_t + \bar{\nu}_t, \qquad (16)$$

where $\bar{v}_t = (v_t', 0, ..., 0)$, $\bar{Q} = \begin{bmatrix} Q & 0 & ... & 0 \\ 0 & 0_{(K+M)} & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & 0_{(K+M)} \end{bmatrix}$. We can also write

$$\mathbf{X}_t = \bar{\mathbf{\Lambda}}\bar{\mathbf{F}}_t + \mathbf{e}_t \qquad (17)$$

where $\bar{\mathbf{\Lambda}} = \begin{bmatrix} \mathbf{\Lambda} & 0 & ... & 0 \end{bmatrix}$. Hence, the system to be estimated is

$$\mathbf{X}_t = \bar{\mathbf{\Lambda}}\bar{\mathbf{F}}_t + \mathbf{e}_t \tag{18}$$

$$\bar{\mathbf{F}}_t = \bar{\Phi}\bar{\mathbf{F}}_{t-1} + \bar{\nu}_t \tag{19}$$

According to the Bayesian approach, we treat the model's parameters $\theta = (\Lambda, R, vec(\Phi'), Q)$ and the factors $\{F_t\}_{t=1}^T$ as random variables. Let $\widetilde{X}_T = (X_{1,...,}X_T)$ and $\widetilde{F}_T = (F_{1,...,}F_T)$ be the histories of $X$ and $F$, respectively. We need to derive the posterior densities of $F$ and $\theta$: $p(\widetilde{F}_T) = \int_\Omega p(\widetilde{F}_T, \theta)d\theta$ and $p(\theta) = \int_{\digamma} p(\widetilde{F}_T, \theta)d\widetilde{F}_T$, where $p(\widetilde{F}_T, \theta)$ is the joint posterior distribution and $\Omega$ and $\digamma$ are the supports of $\theta$ and $F$.

We apply multi-move Gibbs sampling, to obtain an empirical approximation of the joint distribution. We start with an initial set of values, $\theta^0$. Then, conditional on $\theta^0$ and $\widetilde{X}_T$, we draw $\widetilde{F}_T^1$ from the conditional density $p(\widetilde{F}_T \mid \widetilde{X}_T, \theta^0)$ and $\theta^1$ from the conditional distribution $p(\theta \mid \widetilde{X}_T, \widetilde{F}_T^1)$. These steps are repeated for $s$ iterations, until the empirical distributions of $\widetilde{F}_T^s$ and $\theta^s$ have converged. It can be proven that, as $s \to \infty$, under regularity conditions, the marginal and joint distributions of sampled parameters $\left(\widetilde{F}_T^s, \theta^s\right)$ converge to the true distributions $(F_T, \theta)$, at an exponential rate (see Geman and Geman (1994)).

The procedure is as follow.

**1.** Choice of starting value $\theta^0$. It is advisable to start with a dispersed set of parameter values, verifying that they lead to similar empirical distributions. Unless otherwise specified, we use the principal components estimates, transformed to satisfy our normalization.

**2.** How to draw from $p(\widetilde{F}_T \mid \widetilde{X}_T, \theta)$. This conditional distribution can be expressed as the product of conditional distributions:

$$p(\widetilde{F}_T \mid \widetilde{X}_T, \theta) = p(F_T \mid \widetilde{X}_T, \theta) \prod_{t=1}^{T-1} p(F_t \mid F_{t+1}, \widetilde{X}_T, \theta)$$

which is derived, by exploiting the Markov property of the state-space model. The model is linear and Gaussian, therefore we have

$$\begin{gathered} F_T \mid \widetilde{X}_T, \theta \sim N(F_{T|T}, P_{T|T}), \\ F_t \mid F_{t+1}, \widetilde{X}_t, \theta \sim N(F_{t|t+1,F_{t+1}}, P_{t|t,F_{t+1}}), \quad t = T-1, ..., 1, \end{gathered}$$

where

$$\begin{gathered} F_{T|T} = E(F_T \mid \widetilde{X}_T, \theta), \\ P_{T|T} = Cov(F_T \mid \widetilde{X}_T, \theta), \\ F_{t|t+1,F_{t+1}} = E(F_t \mid \widetilde{X}_t, F_{t+1}, \theta) = E(F_t \mid F_{t+1}, F_{t|t}, \theta), \\ P_{t|t,F_{t+1}} = Cov(F_t \mid F_{t+1}, \widetilde{X}_t, \theta) = Cov(F_t \mid F_{t+1}, F_{t|t}, \theta). \end{gathered}$$

Here $F_{t|t}$ refers to the expectation of $F_t$ conditional on information dated $t$ or earlier. We can, then, obtain $F_{t|t}$ and $P_{t|t}$, $t = 1, ..., T$ by Kalman Filter, conditional on $\theta$ and the data $\widetilde{X}_t$, by applying the formulas in Hamilton (1994), for example. From the last iteration, we obtain $F_{T|T}$ and $P_{T|T}$ and using those and (**??**), we can draw $F_t$. Then, we can go backwards through the sample, deriving $F_{T-1|T-1,F_t}$ and $P_{T-1|T-1,F_t}$ by Kalman Filter, drawing $F_{T-1}$ from (**??**), and so on for $F_t$, $t = T-2, T-3, ..., 1$. A modification of the Kalman filter procedure, as described in Kim and Nelson (1999), is necessary when the number of lags $d$ in (14) is greater than 1.

**3.** How to draw from $p(\theta \mid \widetilde{X}_T, \widetilde{F}_T)$. Conditional on the data and on the factors generated by the previous step, we can draw values for $\theta$. As the factors are taken as known, (13) and (14) can be treated as two separate sets of equations, the former specifying the distribution of $\Lambda$ and $R$, the latter that of $vec(\Phi')$ and $Q$. Let's start from (13): we can apply equation-by-equation OLS, to obtain $\widehat{\Lambda}$ and $\widehat{e}$. We have $\widehat{R}_{ii} = \widehat{e}'\widehat{e}/(T - K_i)$, where $K_i$ is the number of regressors in equation $i$, and we set $R_{ij} = 0$, for $i \neq j$. With an uninformative prior, we have

$$R_{ii} \mid \widetilde{X}_T, \widetilde{F}_T = (T - K_i)\,\tfrac{\widehat{R}_{ii}}{x} \text{ where } x \sim \chi^2(T - K_i).$$

After drawing $R_{ii}$, we can draw $\Lambda_i \sim N(\widehat{\Lambda}_i, R_{ii}[\widetilde{F}_T^{(i)\prime}\ \widetilde{F}_T^{(i)}]^{-1})$.

Let's focus now on (14). Here we have a standard VAR system, which can, thus, be estimated equation by equation to get $vec(\widehat{\Phi})$ and $\widehat{Q}$. Then, with a flat prior on $\log|Q|$, we can draw $Q$ from

$$InvWishart\left(\left[(T-d)\widehat{Q}\right]^{-1}, T-(K+M)d\right)$$

and, conditional on the generated $Q$, we draw $vec(\Phi') \sim N(vec(\widehat{\Phi}'), Q \otimes (\widetilde{F}_T'\widetilde{F}_T)^{-1})$, where $vec(\Phi')$ contains the rows of $\Phi'$ in stacked form, forming a vector of length $d(K+M)^2$ and "$\otimes$" refers to the Kronecker product.

Steps 2 and 3 are repeated for each iteration $s$. Then, inference is based on the distribution of $\left(\widetilde{F}_T^s, \theta^s\right)$, after convergence (that is, discarding a big enough number $B$ of initial draws). We calculate medians and percentiles of $\left(\widetilde{F}_T^s, \theta^s\right)$ for $s = B+1, ..., S$ to form estimates of the factors and model parameters and of the associated uncertainty. Also, we evaluate the impulse response functions for each draw and calculate their medians and percentiles.

# C The Data Set.

The data are taken from Stock and Watson (2002), FRED or Datastream.

1. Real Activity Factor.

| | Mnemonic | Description | Source | T |
|---|---|---|---|---|
| 1 | IP | Industrial Production: total index (1992=100,sa) | SW | 5 |
| 2 | IPP | Industrial Production: products, total (1992=100,sa) | SW | 5 |
| 3 | IPF | Industrial Production: final products (1992=100,sa) | SW | 5 |
| 4 | IPC | Industrial Production: consumer goods (1992=100,sa) | SW | 5 |
| 5 | IPCD | Industrial Production: durable consumer goods (1992=100,sa) | SW | 5 |
| 6 | IPCN | Industrial Production: nondurable consumer goods (1992=100,sa) | SW | 5 |
| 7 | IPE | Industrial Production: business equipment (1992=100,sa) | SW | 5 |
| 8 | IPI | Industrial Production: intermediate products (1992=100,sa) | SW | 5 |
| 9 | IPM | Industrial Production: materials (1992=100,sa) | SW | 5 |
| 10 | IPMND | Industrial Production: nondurable goods materials (1992=100,sa) | SW | 5 |
| 11 | IPMFG | Industrial Production: manufacturing (1992=100,sa) | SW | 5 |
| 12 | IPD | Industrial Production: durable manufacturing (1992=100,sa) | SW | 5 |
| 13 | IPN | Industrial Production: nondurable manufacturing (1992=100,sa) | SW | 5 |
| 14 | IPMIN | Industrial Production: mining (1992=100,sa) | SW | 5 |
| 15 | IPUT | Industrial Production: utilities (1992=100,sa) | SW | 5 |
| 16 | IPXMCA | Capacity Util rate: manufacturing, total (% of capacity,sa)(frb) | SW | 1 |
| 17 | GMYXPQ | Personal Income less transfer payments (chained)(#51)(bil92$,saar) | SW | 5 |
| 18 | LHEL | Index of help-wanted advertising in newspapers (1967=100,sa) | SW | 5 |
| 19 | LHELX | Employment: ratio; help-wanted ads: no. unemployed clf | SW | 4 |
| 20 | LHEM | Civilian Labor Force: employed, total (thous.,sa) | SW | 5 |
| 21 | LHNAG | Civilian Labor Force: employed, nonagric. industries (thous.,sa) | SW | 5 |
| 22 | LHUR | Unemployment rate: all workers, 16 years & over (%,sa) | SW | 1 |
| 23 | LHU680 | Unemploy. by duration: average(mean) duration in weeks (sa) | SW | 1 |
| 24 | LHU5 | Unemploy. by duration: persons unempl. less than 5 wks (thous.,sa) | SW | 1 |
| 25 | LHU14 | Unemploy. by duration: persons unempl. 5 to 14 wks (thous.,sa) | SW | 1 |
| 26 | LHU15 | Unemploy. by duration: persons unempl. 15 wks + (thous.,sa) | SW | 1 |
| 27 | LHU26 | Unemploy. by duration: persons unempl. 15 to 26 wks (thous.,sa) | SW | 1 |
| 28 | LPNAG | Employees on nonag. payrolls: total (thous.,sa) | SW | 5 |
| 29 | LP | Employees on nonag. payrolls: total, private (thous.,sa) | SW | 5 |
| 30 | LPGD | Employees on nonag. payrolls: goods-producing (thous.,sa) | SW | 5 |

| | | | | |
|---|---|---|---|---|
| 31 | LPCC | Employees on nonag. payrolls: contract construction (thous.,sa) | SW | 5 |
| 32 | LPEM | Employees on nonag. payrolls: manufacturing (thous.,sa) | SW | 5 |
| 33 | LPED | Employees on nonag. payrolls: durable goods (thous.,sa) | SW | 5 |
| 34 | LPEN | Employees on nonag. payrolls: nondurable goods (thous.,sa) | SW | 5 |
| 35 | LPSP | Employees on nonag. payrolls: service-producing (thous.,sa) | SW | 5 |
| 36 | LPTc | Employees on nonag. payrolls: wholesale & retail trade (thous.,sa) | SW | 5 |
| 37 | LPFR | Employees on nonag. payrolls: finance, insurance & real estate (thous.,sa) | SW | 5 |
| 38 | LPS | Employees on nonag. payrolls: services (thous.,sa) | SW | 5 |
| 39 | LPGOV | Employees on nonag. payrolls: government (thous.,sa) | SW | 5 |
| 40 | LPHRM | Avg. weekly hrs. of prod. wkrs.: manufacturing (sa) | SW | 1 |
| 41 | LPMOSA | Avg. weekly hrs. of prod. wkrs.: mfg, overtime hrs. (sa) | SW | 1 |
| 42 | MSMTQ | Manufacturing & trade: total (mil of chained 1992 dollars)(sa) | SW | 5 |
| 43 | MSMQ | Manufacturing & trade: manufacturing; total (mil of chained 1992 dollars)(sa) | SW | 5 |
| 44 | MSDQ | Manufacturing & trade: mfg; durable goods (mil of chained 1992 dollars)(sa) | SW | 5 |
| 45 | MSNQ | Manufacturing & trade: mfg; nondurable goods (mil of chained 1992 dollars)(sa) | SW | 5 |
| 46 | WTQ | Merchant wholesalers: total (mil of chained 1992 dollars)(sa) | SW | 5 |
| 47 | WTDQ | Merchant wholesalers: durable goods total (mil of chained 1992 dollars)(sa) | SW | 5 |
| 48 | WTNQ | Merchant wholesalers: nondurable goods total (mil of chained 1992 dollars)(sa) | SW | 5 |
| 49 | RTQ | Retail trade: total (mil of chained 1992 dollars)(sa) | SW | 5 |
| 50 | RTNQ | Retail trade: nondurable goods (mil of chained 1992 dollars)(sa) | SW | 5 |
| 51 | GMCQ | Personal consumption expend (chained)-total (bil 92$,saar) | SW | 5 |
| 52 | GMCDQ | Personal consumption expend (chained)-total durables (bil 92$,saar) | SW | 5 |
| 53 | GMCNQ | Personal consumption expend (chained)-total nondurables (bil 92$,saar) | SW | 5 |
| 54 | GMCSQ | Personal consumption expend (chained)-services (bil 92$,saar) | SW | 5 |
| 55 | GMCANQ | Personal consumption expend (chained)-new cars (bil 92$,saar) | SW | 5 |
| 56 | HSFR | Housing starts: nonfarm (1947-58); total farm&nonfarm (1959-)(thous.,sa) | SW | 4 |
| 57 | HSNE | Housing starts: northeast (thous.u.) s.a. | SW | 4 |
| 58 | HSMW | Housing starts: midwest (thous.u.) s.a. | SW | 4 |
| 59 | HSSOU | Housing starts: south (thous.u.) s.a. | SW | 4 |
| 60 | HSWST | Housing starts: west (thous.u.) s.a. | SW | 4 |
| 61 | HSBR | Housing authorized: total new priv housing units (thous.,saar) | SW | 4 |
| 62 | HMOB | Mobile homes: manufacturers'shipments (thous. of u., saar) | SW | 4 |
| 63 | IVMTQ | Manufacturing & trade inventories: total (mil of chained 1992)(sa) | SW | 5 |
| 64 | IVMFGQ | Inventories, business, mfg (mil of chained 1992 dollars,sa) | SW | 5 |
| 65 | IVMFDQ | Inventories, business durables (mil of chained 1992 dollars,sa) | SW | 5 |
| 66 | IVMFNQ | Inventories, business, nondurables (mil of chained 1992 dollars,sa) | SW | 5 |
| 67 | IVWRQ | Manufacturing & trade inventories: merchant wholesalers (mil of chained 1992)(sa) | SW | 5 |
| 68 | IVRRQ | Manufacturing & trade inventories: retail trade (mil of chained 1992)(sa) | SW | 5 |

| | | | | |
|---|---|---|---|---|
| 69 | IVSRQ | Ratio for mfg & trade: inventory/sales (chained 1992 dollars,sa) | SW | 2 |
| 70 | IVSRMQ | Ratio for mfg & trade: mfg; inventory/sales (87$)(sa) | SW | 2 |
| 71 | IVSRWQ | Ratio for mfg & trade: wholesaler; inventory/sales (87$)(sa) | SW | 2 |
| 72 | IVSRRQ | Ratio for mfg & trade: retail trade; inventory/sales (87$)(sa) | SW | 2 |
| 73 | MOCMQ | New orders (net)-consumer goods & materials, 1992 dollars (bci) | SW | 5 |
| 74 | MDOQ | New orders, durable goods industries, 1992 dollars (bci) | SW | 5 |
| 75 | MSONDQ | New orders, nondefense capital goods, 1992 dollars (bci) | SW | 5 |
| 76 | MO | mfg new orders: all manufacturing industries, total (mil$,sa) | SW | 5 |
| 77 | MOWU | mfg new orders: mfg industries with unfilled orders, total (mil$,sa) | SW | 5 |
| 78 | MDO | mfg new orders: durable goods industries, total (mil$,sa) | SW | 5 |
| 79 | MDUWU | mfg new orders: durable goods indust with unfilled orders, total (mil$,sa) | SW | 5 |
| 80 | MNO | mfg new orders: nondurable goods industries, total (mil$,sa) | SW | 5 |
| 81 | MNOU | mfg new orders: nondurable goods ind with unfilled orders, total (mil$,sa) | SW | 5 |
| 82 | MU | mfg unfilled orders: all manufacturing industries, total (mil$,sa) | SW | 5 |
| 83 | MDU | mfg unfilled orders: durable goods industries, total (mil$,sa) | SW | 5 |
| 84 | MNU | mfg unfilled orders: nondurable goods industries, total (mil$,sa) | SW | 5 |
| 85 | MPCON | contracts & orders for plant & equipment (bil$,sa) | SW | 5 |
| 86 | MPCONQ | contracts & orders for plant & equipment in 1992 dollars (bci) | SW | 5 |
| 87 | DSPIC96 | Real Disposable Personal Income | FRED | 5 |
| 88 | EMRATIO | Civilian Employment-Population Ratio | FRED | 5 |
| 89 | CIVPART | Civilian Participation Rate | FRED | 5 |
| 90 | USSHIM..A | US Shipments - All Manufacturing Industries (disc.) CURN | Datastream | 5 |

2. Inflation Factor.

| | | | | |
|---|---|---|---|---|
| 91 | PWFSA | Producer price index: finished goods (82=100,sa) | SW | 5 |
| 92 | PWFCSA | Producer price index: finished consumer goods (82=100,sa) | SW | 5 |
| 93 | PSM99Q | Index of sensitive materials prices (1990=100)(bci-99a) | SW | 5 |
| 94 | PUNEW | CPI-U: all items (82-84=100,sa) | SW | 5 |
| 95 | PU83 | CPI-U: apparel & upkeep (82-84=100,sa) | SW | 5 |
| 96 | PU84 | CPI-U: transportation (82-84=100,sa) | SW | 5 |
| 97 | PU85 | CPI-U: medical care (82-84=100,sa) | SW | 5 |
| 98 | PUC | CPI-U: commodities (82-84=100,sa) | SW | 5 |
| 99 | PUCD | CPI-U: durables (82-84=100,sa) | SW | 5 |
| 100 | PUS | CPI-U: services (82-84=100,sa) | SW | 5 |
| 101 | PUXF | CPI-U: all items less food (82-84=100,sa) | SW | 5 |
| 102 | PUXHS | CPI-U: all items less shelter (82-84=100,sa) | SW | 5 |
| 103 | PUXM | CPI-U: all items less medical care (82-84=100,sa) | SW | 5 |

| | | | | |
|---|---|---|---|---|
| 104 | GMDC | PCE, impl. price defl.: pce (1987=100) | SW | 5 |
| 105 | GMDCD | PCE, impl. price defl.: pce; durables (1987=100) | SW | 5 |
| 106 | GMDCN | PCE, impl. price defl.: pce; nondurables (1987=100) | SW | 5 |
| 107 | GMDCS | PCE, impl. price defl.: pce; services (1987=100) | SW | 5 |
| 108 | LEHCC | Avg. hr earnings of constr wkrs: construction ($,sa) | SW | 5 |
| 109 | LEHM | Avg. hr earnings of prod wkrs: manufacturing ($,sa) | SW | 5 |
| 110 | PFCGEF | Producer Price Index: Finished Consumer Goods Excluding Foods | FRED | 5 |
| 111 | PPICPE | Producer Price Index Finished Goods: Capital Equipment | FRED | 5 |
| 112 | PPICRM | Producer Price Index: Crude Materials for Further Processing | FRED | 5 |
| 113 | PPIFCF | Producer Price Index: Finished Consumer Foods | FRED | 5 |
| 114 | PPIITM | Producer Price Index: Intermediate Materials: Supplies & Components | FRED | 5 |
| 115 | OILPRICE | Spot Oil Price: West Texas Intermediate | FRED | 5 |
| 116 | USLABCOSE | US Unit Labor Costs in Manufacturing, Index (BCI 62) sadj | Datastream | 5 |

3. Interest Rates Factor.

| | | | | |
|---|---|---|---|---|
| 117 | FYGT5 | Interest rate: US Treasury const maturities 5-yr (% per ann,nsa) | SW | 1 |
| 118 | FYGT10 | Interest rate: US Treasury const maturities 10-yr (% per ann,nsa) | SW | 1 |
| 119 | FYAAAC | Bond yield: moody's aaa corporate (% per annum) | SW | 1 |
| 120 | FYBAAC | Bond yield: moody's baa corporate (% per annum) | SW | 1 |
| 121 | FYFHA | Secondary market yields on fha mortgages (% per annum) | SW | 1 |
| 122 | GS1 | 1-Year Treasury Constant Maturity Rate | FRED | 1 |
| 123 | GS3 | 3-Year Treasury Constant Maturity Rate | FRED | 1 |
| 124 | LTGOVTBD | Long-Term U.S. Government Securities | FRED | 1 |
| 125 | TB3MS | 3-Month Treasury Bill: Secondary Market Rate | FRED | 1 |
| 126 | TB6MS | 6-Month Treasury Bill: Secondary Market Rate | FRED | 1 |

4. Financial Market Factor.

| | | | | |
|---|---|---|---|---|
| 127 | FSNCOM | NYSE common stock price index: composite (12/31/65=50) | SW | 5 |
| 128 | FSPCOM | S&P's common stock price index: composite (1941-43=10) | SW | 5 |
| 129 | FSPIN | S&P's common stock price index: industrials (1941-43=10) | SW | 5 |
| 130 | FSPCAP | S&P's common stock price index: capital goods (1941-43=10) | SW | 5 |
| 131 | FSPUT | S&P's common stock price index: utilities (1941-43=10) | SW | 5 |
| 132 | FSDXP | S&P's composite common stock: dividend yield (% per annum) | SW | 1 |
| 133 | FSPXE | S&P's composite common stock: price-earnings ratio (%,nsa) | SW | 1 |
| 134 | USSHRPRCF | US Dow Jones Industrials Share Price Index (EP) | Datastream | 5 |

5. Money Factor.

| | | | | |
|---|---|---|---|---|
| 135 | FM1 | Money stock: m1 (curr,trav.cks,dem dep,other ck'able dep)(bil$,sa) | SW | 5 |
| 136 | FM2 | Money stock: m2 (m1+o'nite rps,euro$,g/p&b/d mmmfs&sav&sm time dep)(bil$,sa) | SW | 5 |
| 137 | FM3 | Money stock: m3 (m2+lg time dep,term rp's&inst only mmmfs)(bil$,sa) | SW | 5 |
| 138 | FM2DQ | Money-supply-m2 in 1992 dollars (bci) | SW | 5 |
| 139 | FMFBA | Monetary base, adj for reserve requirement changes (mil$,sa) | SW | 5 |
| 140 | FMRRA | Depository inst reserves: total,adj for reserve req chgs (mil$,sa) | SW | 5 |
| 141 | FMRNBC | Depository inst reserves: nonborrow+ext cr,adj for res req chgs (mil$,sa) | SW | 5 |
| 142 | BOGNONBR | Non-Borrowed Reserves of Depository Institutions | FRED | 5 |
| 143 | CURRDD | Currency Component of M1 Plus Demand Deposits | FRED | 5 |
| 144 | CURRSL | Currency Component of M1 | FRED | 5 |
| 145 | DEMDEPSL | Demand Deposits at Commercial Banks | FRED | 5 |
| 146 | EXCRESNS | Excess Reserves of Depository Institutions | FRED | 2 |
| 147 | LGTDCBSL | Large Time Deposits at Commercial Banks | FRED | 5 |
| 148 | LTDSL | Large Time Deposits - Total | FRED | 5 |
| 149 | NFORBRES | Net Free or Borrowed Reserves of Depository Institutions | FRED | 2 |
| 150 | REQRESNS | Required Reserves, Not Adjusted for Changes in Reserve Requirements | FRED | 5 |
| 151 | RESBALNS | Reserve Balances with Federal Reserve Banks, Not Adj for Changes in Res Reqs | FRED | 5 |
| 152 | SAVINGSL | Savings Deposits - Total | FRED | 5 |
| 153 | STDCBSL | Small Time Deposits at Commercial Banks | FRED | 5 |
| 154 | STDSL | Small Time Deposits - Total | FRED | 5 |
| 155 | SVGCBSL | Savings Deposits at Commercial Banks | FRED | 5 |
| 156 | SVSTCBSL | Savings and Small Time Deposits at Commercial Banks | FRED | 5 |
| 157 | SVSTSL | Savings and Small Time Deposits - Total | FRED | 5 |
| 158 | TCDSL | Total Checkable Deposits | FRED | 5 |
| 159 | TOTTDP | Total Time and Savings Deposits at All Depository Institutions | FRED | 5 |

6. Credit Factor.

| | | | | |
|---|---|---|---|---|
| 160 | AUTOSL | Total Automobile Credit Outstanding | FRED | 5 |
| 161 | BUSLOANS | Commercial and Industrial Loans at All Commercial Banks | FRED | 5 |
| 162 | CONSUMER | Consumer (Individual) Loans at All Commercial Banks | FRED | 5 |
| 163 | INVEST | Total Investments at All Commercial Banks | FRED | 5 |
| 164 | LOANINV | Total Loans and Investments at All Commercial Banks | FRED | 5 |

| | | | | |
|---|---|---|---|---|
| 165 | LOANS | Total Loans and Leases at Commercial Banks | FRED | 5 |
| 166 | NONREVSL | Total Nonrevolving Credit Outstanding | FRED | 5 |
| 167 | OTHERSL | Total Other Credit Outstanding | FRED | 5 |
| 168 | OTHSEC | Other Securities at All Commercial Banks | FRED | 5 |
| 169 | REALLN | Real Estate Loans at All Commercial Banks | FRED | 5 |
| 170 | TOTALSL | Total Consumer Credit Outstanding | FRED | 5 |

7. Expectations.

| | | | | |
|---|---|---|---|---|
| 171 | PMI | Purchasing managers'index (sa) | SW | 1 |
| 172 | PMP | NAPM production index (percent) | SW | 1 |
| 173 | PMEMP | NAPM employment index (percent) | SW | 1 |
| 174 | PMNV | NAPM inventories index (percent) | SW | 1 |
| 175 | PMNO | NAPM new orders index (percent) | SW | 1 |
| 176 | PMDEL | NAPM vendor deliveries index (percent) | SW | 1 |
| 177 | PMCP | NAPM commodity prices index (percent) | SW | 1 |
| 178 | HHSNTN | U.of Mich. index of consumer expectations (bcd-83) | SW | 1 |
| 179 | sFYCP90 | Spread sFYCP90-Fedfund | SW | 1 |
| 180 | sFYGM3 | Spread sFYGM3-Fedfund | SW | 1 |
| 181 | sFYGM6 | Spread sFYGM6-Fedfund | SW | 1 |
| 182 | sFYGT1 | Spread sFYGT1-Fedfund | SW | 1 |
| 183 | sFYGT5 | Spread sFYGT5-Fedfund | SW | 1 |
| 184 | sFYGT10 | Spread sFYGT10-Fedfund | SW | 1 |

8. Federal Funds Rate.

| | | | | |
|---|---|---|---|---|
| 185 | FEDFUNDS | Effective Federal Funds Rate | FRED | 1 |

*Note*: T is the transformation code: 1=no transformation, 2=first difference, 4=logarithm, 5=first difference of logarithms.

| Sample | Partial-Adjustment $\rho$ | Response to inflation $\phi^{\pi}$ | Response to real activity $\phi^{y}$ |
|---|---|---|---|
| 1960:01-1998:12 | 0.957 (0.013) | 1.214 (0.257) | 1.205 (0.420) |

Table 1 - Estimated Policy Reaction Function (Taylor Rule).

| | | Response to Structural Factors | | | | |
|---|---|---|---|---|---|---|
| Sample | $\rho$ | Real Activity | Inflation | Financial Market | Money | Credit |
| 1960:01-1998:12 | 0.951* (0.013) | 0.980* (0.35) | 1.685* (0.316) | 0.723* (0.269) | 0.158 (0.113) | 0.187 (0.276) |

Table 2 - Estimated Policy Reaction Function with Structural Factors.

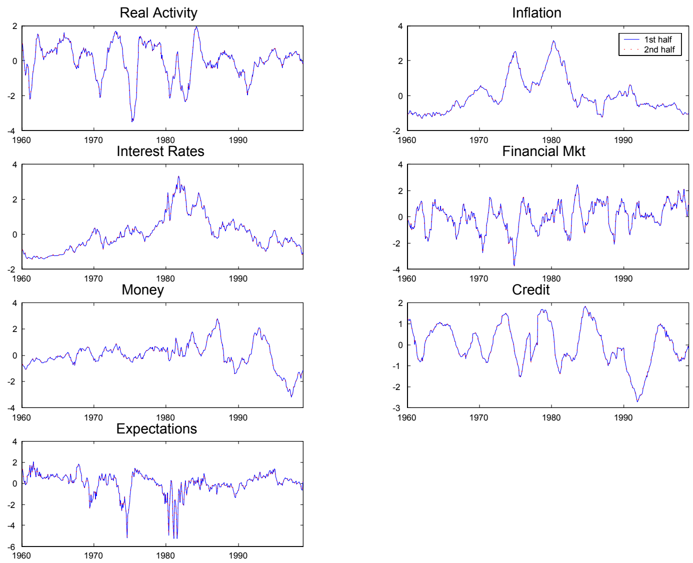


Figure 1 - Convergence: estimated factors first half vs. second half of the sampling.

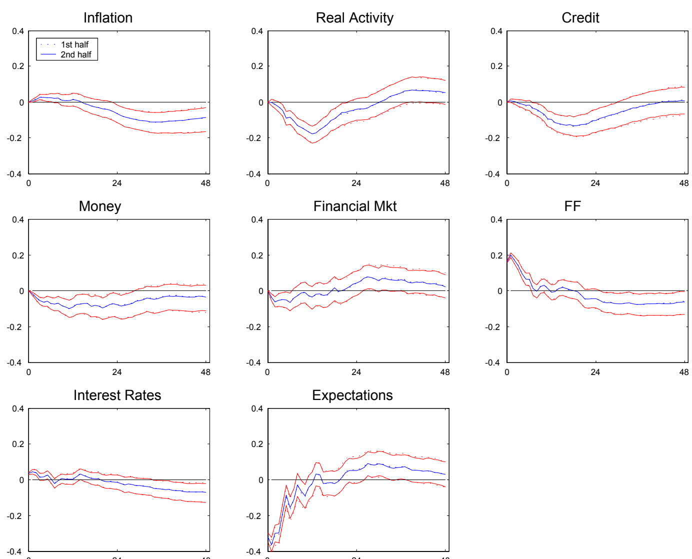


Figure 2 - Convergence: impulse response functions, first and second half.

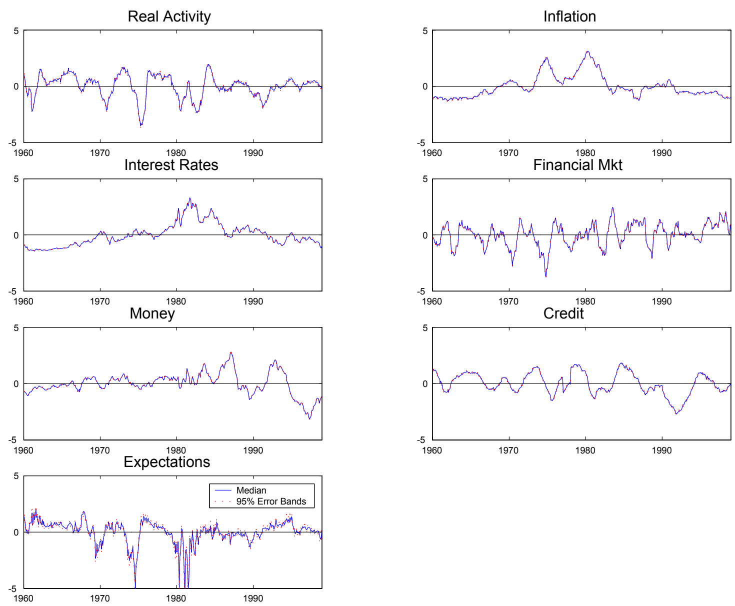


Figure 3 - Estimated structural factors with error bands.

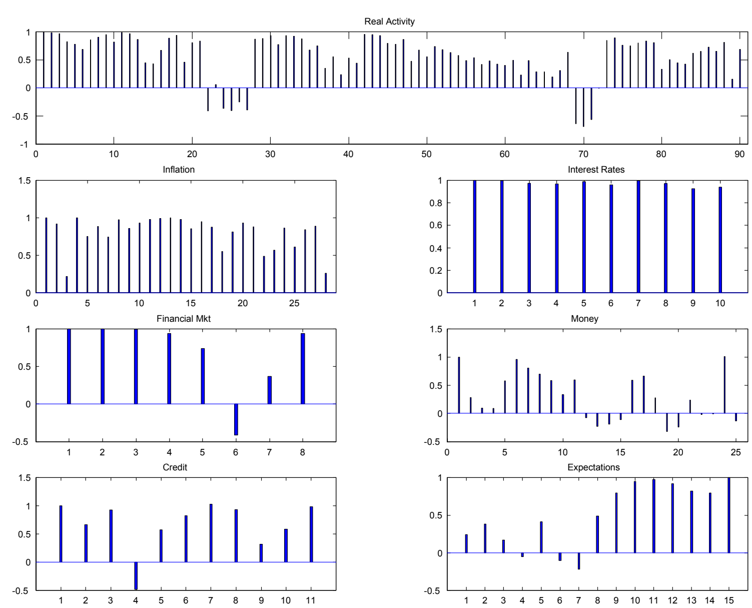


Figure 4 - Estimated loadings.

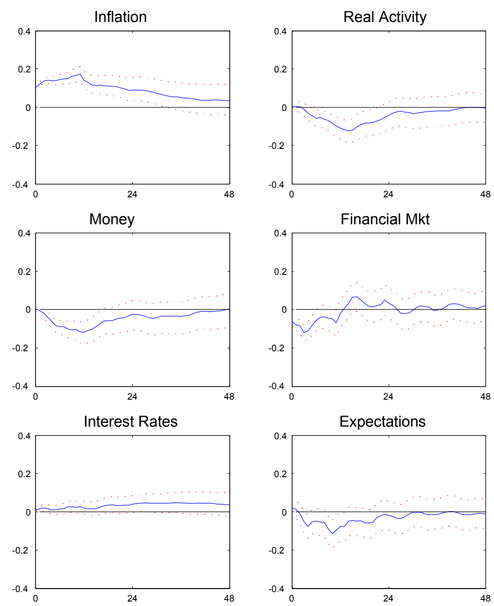


Figure 5 - Impulse responses to one std. shock to Inflation factor.

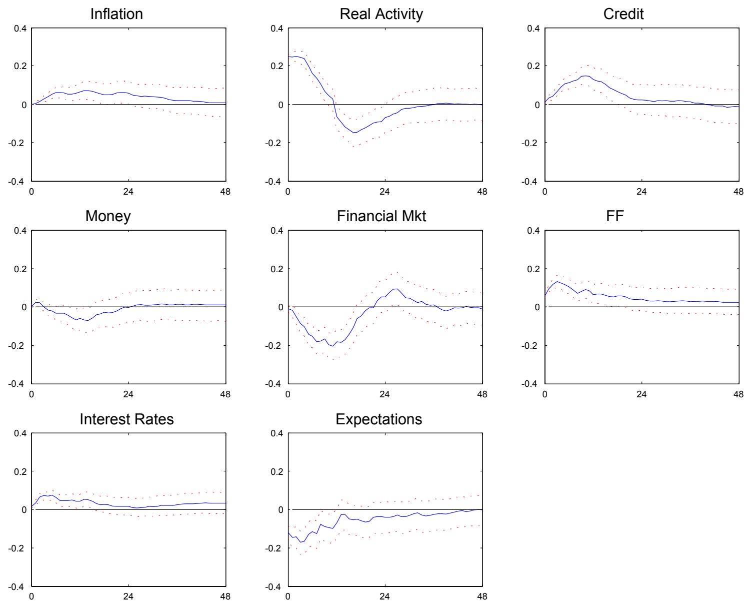


Figure 6 - Impulse responses to one std. shock to Real Activity factor.

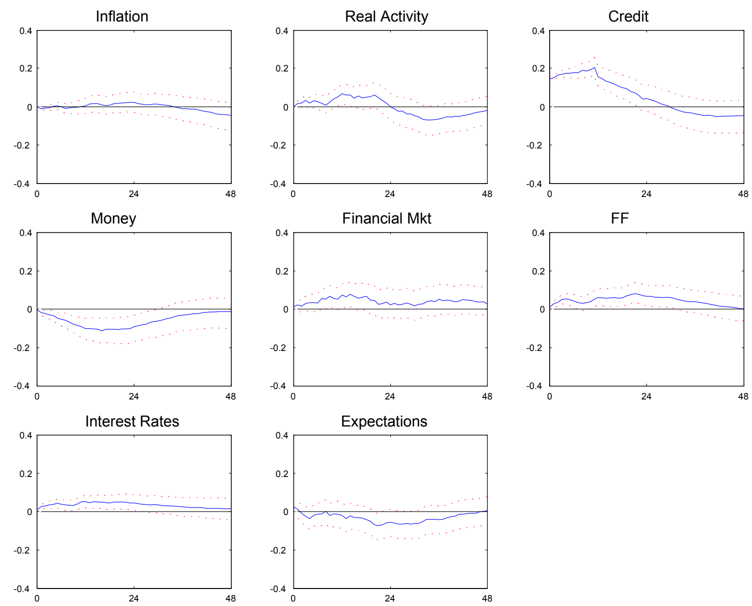


Figure 7 - Impulse responses to one std. shock to Credit factor.


Figure 8 - Impulse responses to one std. shock to Money factor.

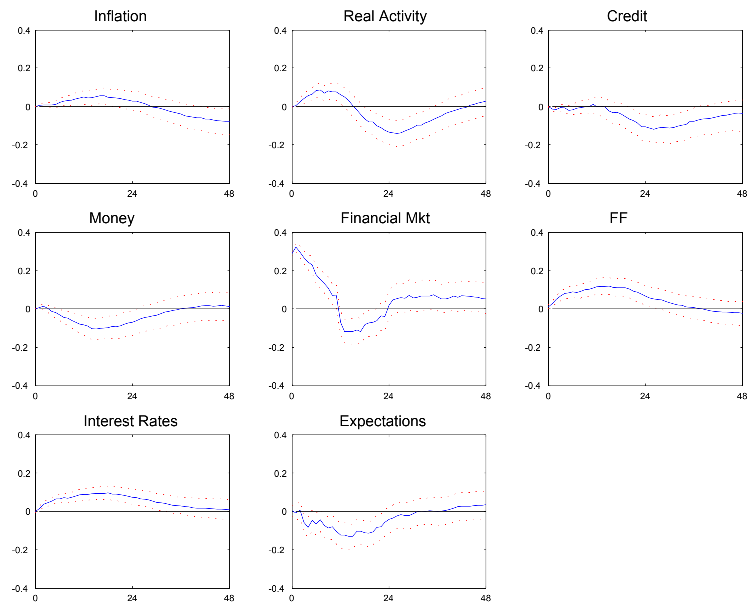


Figure 9 - Impulse responses to one std. shock to Financial Market factor.

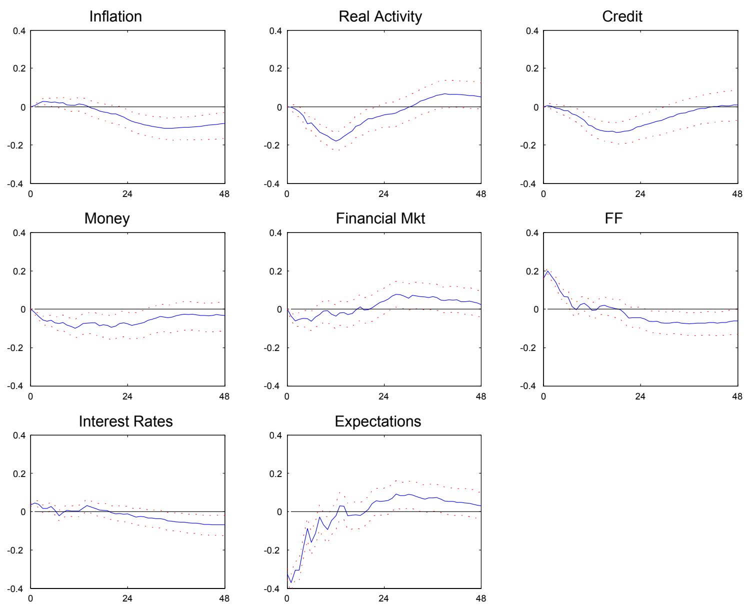


Figure 10 - Impulse responses to one std. shock to Federal Funds Rate.

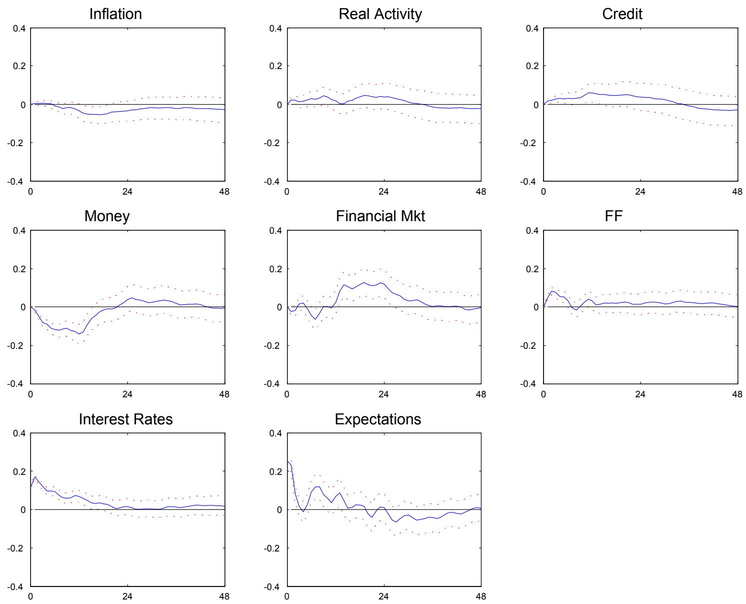


Figure 11 - Impulse responses to one std. shock to Interest Rate factor.

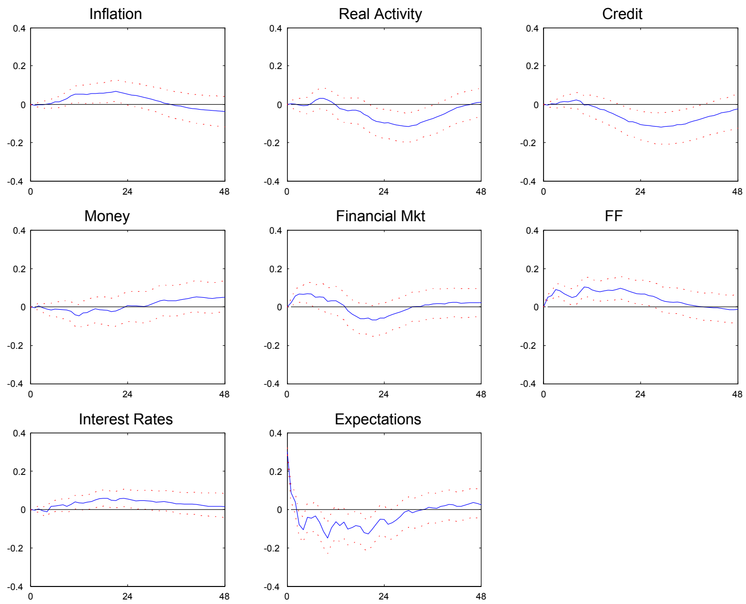


Figure 12 - Impulse responses to one std. shock to Expectations factor.

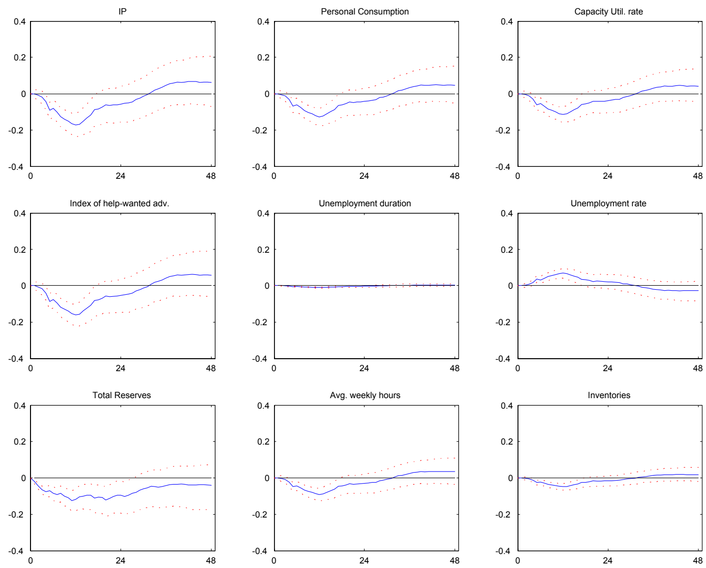


Figure 13 - Impulse responses to a monetary policy shock of various variables.

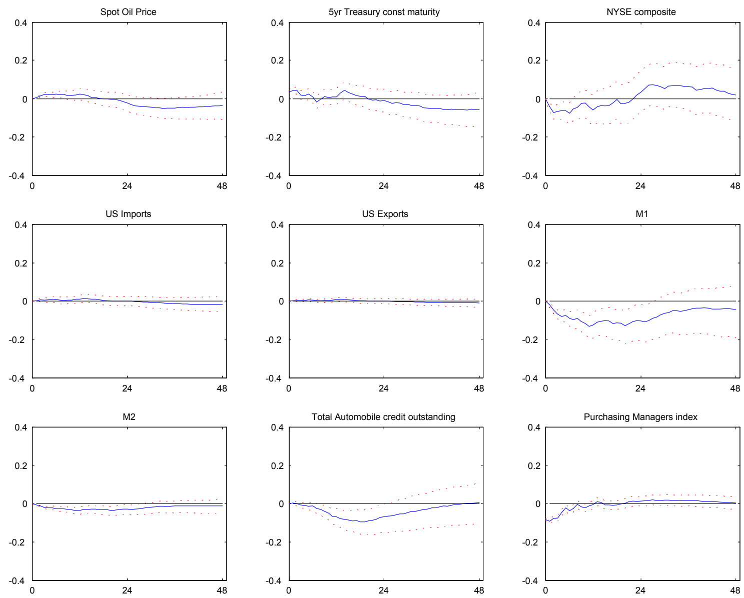


Figure 14 - Impulse responses to a monetary policy shock of various variables.